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RESEARCH ARTICLE

Methods of Optimization of Mining Operations in a Deep Mine–Tracking the Dynamic Overloads Using IoT Sensor

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ABSTRACT Self-propelled machines are the main resources used by the Polish copper ore mining industry to transport ore from the mining area to reloading points for conveyor transport. Due to the difficult mining conditions, they must meet high requirements in terms of operational efficiency, safety, and reliability. One of the most significant challenges is high robustness to dynamic overloads. In practice, they have a strong dependency on pavement influence during machine movement, the type of operation, and the driving style of the operator. In this research, we focus on the multivariate analysis of dynamic overloads observed on a large population of haul trucks operating in different mining areas. The main aim of this study was the identification of major factors of excessive dynamic overload that result in damage to structural nodes of machines. In the case of haul track, the joint is such a critical component, that in extreme situations, it breaks and splits the machine in two. There are proposed methods for assessing the occurrence of dynamic overload based on recognized mining conditions and operator behavior. In addition, we propose a method to specify which factors are more meaningful for dynamic overloads. A measurement campaign has been conducted using a mobile inertial sensor interconnected with a developing IoT platform for predictive maintenance of mining infrastructure.

INDEX TERMS Dynamic overloads, self-propelled machine, haul truck, IoT, inertial sensor, underground mining, joint damage.

I. INTRODUCTION

Machine availability and safety in the mine are key aspects that are constantly being optimized. For this reason, predictive maintenance is one of the main developing directions in the mining industry. A rather neglected issue so far concerns the monitoring of the road condition (surface quality, slope, potholes) and its impact on the presence of dynamic loads in underground mining. Poor quality of the road in connection with an incorrect adaptation of driving style to operating conditions can lead to high intensity dynamic overloads with a shock character. Basically, the design parameters of the machines given by the manufacturer assume the ability to overcome much greater dynamic overloads than occur in typical conditions in an underground mine. However, practice shows that it is not always possible to maintain the desired state. It is also related to the occupancy of the machinery park in a given mining division, the topography of the mine, and the type of rock that builds the road. Excessive overloads during operation significantly reduce the durability of structural joints. Such a case is the joint of the haul track. Its damage is typically fatigue. In the first phase, there is a looseness in the connection, which results in micro-damage. Its further propagation causes a crack of the entire horizontal pivot [1]. Exemplary damaged cases have been presented in Fig. 1.

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FIGURE 1. **Breakage of the horizontal pivot – damage to the joint.**

Replacing the joint is one of the most expensive maintenance tasks. A failure that halves a machine is an extremely undesirable event. When it comes to adjusting the design parameters, the possibilities are also limited because of the set wheel dimensions, maximum machine height, expected turning ability, travel speed of the machine, and volume of the cargo box. However, there is a large correlation between the intensity of the failure under consideration and the mining condition. In the case of large multi-site mining enterprises such as KGHM Polska-Miedź (KGHM Polish Copper), such failures were actually associated with specific mining departments. One of the preventive actions was the periodic tightening of a mechanical nut to eliminate the looseness in the connection. Next, a hydraulic nut has been applied for the automatic correction. This solution significantly mitigates the impact of dynamic overloads. Other research has also been directed towards the development of methods for diagnosing backlash in the joint [2]. The road quality assessment method based on inertial measurements was also developed [3].

This study focuses mainly on the analysis of dynamic overload factors to which the machine is exposed during typical transport operations. In the mining industry, there are used machines and installations whose size and weight strongly exceed the size and weight of objects in other industrial branches. The scale of these objects determines their dynamics and external characteristics, including loads with large energy at low frequencies and low cycles. Exemplary recognition of dynamic overloads with a low cycle of influence on heavy-duty machines in the example of a multi-bucket excavator is presented in [4]. As the authors point out, the vibrations of the heavy duty machines are a major factor that has an impact on the reliability of the load-bearing structure. Common calculation instructions known from the literature do not assume the coefficients of dynamic effects. In the majority of cases, the operation conditions introduce more energy into construction than the set calculation level. Identification of relationships between the dynamics of load-bearing structure and the variability of chassis load is necessary to gain more information about the cause of elements' fatigue. On this basis, the definition of modified methods for durability calculation is possible. Mining machine dynamics is one of the crucial steps in the design process.

In the case of mining machines, operating loads very often have a shock character [5], [6], [7]. The transport system and technological movements (such as driving, rotation, and lifting) are key factors of shocks for each kind of machine. For wheeled vehicles, the load level depends on the interaction of the complex system: vehicle (body, chassis, tires) ↔ internal equipment ↔ environment (mainly road conditions) ↔ external load ↔ operator (mainly driving style), Fig. 2 [8].

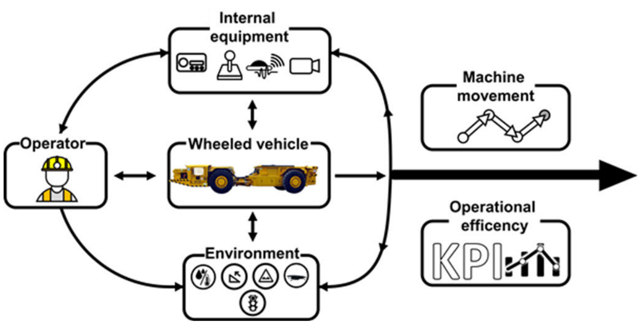


FIGURE 2. **Scheme of interaction for the main dynamic overload factors in relation to: wheeled vehicle – operator – internal equipment – environment [1].**

Operating loads of an impulse nature have a significant impact on the vehicle's technical condition, its internal equipment, and the psychophysical state of the driver [9]. The wheeled vehicles moving on the roads (especially with high amplitudes of pavement profile variability) are constantly exposed to dynamic influences [10]. Investigated loads have a complicated structure, and they reveal differences in terms of values, duration, intensity, or direction of force (vertical, horizontal, or longitudinally). Basically, they depend on:

- High and varied in time driving resistance resulting from road conditions and observed force reactions.
- Operation of rotational elements (drive system, engine).
- Inertia forces (skidding, driving around a curve, rapid acceleration).
- Dynamic loads occur as a result of moving at high speed in varied pavement conditions (especially over bumps) [9].

Considering self-propelled machines, there are also other external sources of dynamic overloads that are connected with the machine, like the operation regime, a condition in the mining area, unexpected events, etc. The most important are: the loading and unloading of bucket/cargo box; driving with a full bucket/cargo box; the machine hitting the wall; and the impact of a lump of rock against the machine housing. More extreme cases are tire bursts, the collapse of the excavation roof, collisions with other machines, or the detonation of a misfire. In the mining area with a low roof, the situation when the loader bucket presses the cargo box during the loading process is very common.

The aim of this paper is to analyze dynamic overloads in terms of factors like workplace conditions, the operator's driving style, operations performed, vehicle equipment, and the occurrence of failures. It has been proven many times that dynamic overloads negatively affect the health of the machine and can lead to serious damage. It has been proven many times that dynamic overloads negatively affect the health of the machine and can lead to serious damage. By establishing which factors cause the highest dynamic overloads, one can introduce countermeasures like driving policies. The effects of which should be visible in a long time window by improving the general condition of machines and reducing the number of unannounced failures.

The article is structured as follows. Section II presents the related works. In Section III, a description of the research is presented. The methodology used for the analysis is included in Section IV. Section V contains a definition of the model for detecting turns, a description of operator evaluation, a presentation of the statistics used, and the factor model explanation. Section VI presents the actual data analysis, and Section 7 contains a summary and conclusions.

II. RELATED WORK

Generally, research oriented toward factors and consequences of dynamic loads influence on mechanical vehicles has been conducted for many years. Unfortunately, they mainly concern light weight vehicles and are usually focused on the load's impact on the operator [11]. The assumptions of research very often deviate from real machine operational conditions and do not include the variability of pavement height profiles.

Parameterization of vibrations recorded while the machine is moving in the excavation allows for the acquisition of characteristics and comparative indices. The methods of assessment for road quality known in the literature have been described in [1]. So far, experimental results have shown that the characteristics of the chassis, the increase in driving speed, the type of road surface, and the degree of bumpiness have a key impact on the increase in dynamic overloads. The same conclusions have been drawn by [9] during the study of combat vehicle types, considering them also as a heavy-duty machines. In this study, the authors used the measurement of vertical accelerations of the hull element, pressures acting on the vehicle hull elements, and deformations occurring at its bottom. Various measurement points have been defined. The level of temporary dynamic loads occurring on the elements of the driving system, resulting from the impact of the road surface, is most often modeled with the peak values of the amplitudes of their vertical acceleration [9], [12], [13]. In order to determine the level of vibration energy of vehicle components, there are also known in practice quantitative measures such as the RMS value of changes in vertical accelerations [14], [15]. An effective parameter for comparative analysis of the level and frequency structure of vibrations of machine components resulting from road conditions is the power spectral density calculated from vertical accelerations [15]. Similar research has been presented by the authors of a paper [16] where an off-road passenger vehicle was investigated. They used measurements of the acceleration and deflection of the front axle suspension and the acceleration of the body frame for various road conditions. They determined comparative indicators as well as presented statistics describing the level and frequency structure of dynamic loads occurring on the chassis as a result of driving on a road with a variable height of the ground profile. The study used the average of the 10 highest values: accelerations measured respectively on the driving axle (a) and separately on the frame (b) and suspension deflection (c), then RMS accelerations recorded on the driving axle (d) and frame (e), and PSD measured on the driving axle (f) and on the frame (g). In turn, in research [17], the author conducted advanced research related to the analysis of the impact of filling the dump truck's cargo box and the unevenness of transport roads on the dynamic forces of the elements acting on the dump truck operated in an opencast mine. The main purpose of the research was to identify the interaction of the road with the dump truck as well as the reaction of the road to dynamic loads observed on the machine. Many articles raise the question of operators' driving style assessment [18], [19], [20], [21], [22] and road condition classification [23], [24].

III. DESCRIPTION OF RESEARCH

The presented research was part of a complex study oriented toward finding the main cause of intensified damages to joints of haul trucks in strictly defined mining areas. To achieve this goal, a massive measurement campaign was carried out covering 3 KGHM copper mines (Lubin, Rudna, and Polkowice-Sieroszowice mines). This action resulted in the collection of over 192 measurement samples from almost 20 haul trucks, giving a total of 2462 recorded work hours. During this research, it has been proven that the dynamic overloads were the main cause of the damage, and a method for early fault detection was introduced [2]. However, preventive actions are needed to address this problem, which is the motivation for this study. In this section, the details about the object of interest, sensor specification, and experimental data gathered are presented.

A. INVESTIGATED TECHNICAL OBJECT

The investigated technical object is a haul truck. All machines included in the experimental work were produced by the same manufacturer. Basically, two types of vehicles were tested, which do not differ significantly in their design. The weight of the exemplary machine is roughly 25 Mg with a nominal payload of up to 25 Mg. Its approximate dimensions are around 3 m wide, about 10 m long, and 2 m high. The machine can move at a maximum speed of 25 km/h (in 4th gear). The vehicle's main task is to haul the excavated material between mining faces and department dumping points. It is possible to indicate four typical operations in every individual cycle of ore transport: (a) loading of the cargo box at the mining face; (b) driving with a full box; (c) dumping material onto a grid (screen) in the department transshipment point; and (d) driving with an empty box back to the loading zone. The considered haul truck, along with the general design scheme and more detailed 3D visualization of the joint, is presented in Fig. 3.

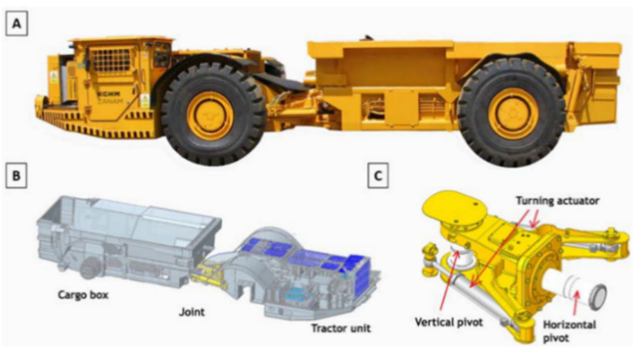


FIGURE 3. General type of haul trucks participating in the experiments (A), general construction view of the machine (B), close up structural view of the turning mechanism (C).

The machines that took part in the experiments were structurally adapted to work in difficult underground mine conditions. The research conducted concerns a specific test object, which is heavy machinery operated in underground tunnels 1 km below the surface. Although the assumed research methodology may seem appropriate for this group of machines, according to the authors, it can be successfully applied by analogy to other types of wheeled machines providing the transport process because the considered operational issue is common among them. Differences may be noticeable in the size of the measured parameters and their impact on the efficiency and technical condition of the machine.

B. THE SENSORS SPECIFICATION

In the thesis of our study, we expressed our belief that the use of a mobile inertial sensor will ensure tracking of the haulage process, identification of dynamic overloads, and operational contexts occurring during the movement of the machine from point A to point B (road gradient, turn at the intersection, road quality) and forces acting on the joint or loosening identification itself. Further synthesis of this information will provide access to valuable knowledge in the fields of machine performance, operational conditions, the course of machine movement in mining excavations, the driving style of operators, and finally their impact on dynamic overloads. Further comparative and factor analysis can be used to identify the main causes of cracking of horizontal pivots, which are crucial to further drawing design and operation recommendations aimed at mitigating dynamic overloads.

Thus, it was decided to apply inertial sensors in our study. Two of these sensors were mounted on each of the machines that took part in the experiments. Due to warranty issues, it was necessary to use non-invasive IMU sensors with their own energy source. To protect them from damage and minimize the influence of the environment, each of the sensors was covered in a steel housing. The first measuring device was located on the working unit (back) and the second on the driving unit (front). The sensors used in the measurement campaign were the x-io Technologies NGIMU (New Generation Inertial Measurement Unit). Such a device includes a triple axis: a gyroscope, an accelerometer, a magnetometer, and a humidity measurement (giving a total of 10 degrees of freedom). The sensor specification declares a 400 Hz sampling rate for each of the triple axis variables; however, the real sampling rate is closer to a stable 360 Hz. The NGIMU Sensor, along with the mounting positions and steel housing, is presented in Fig. 4.

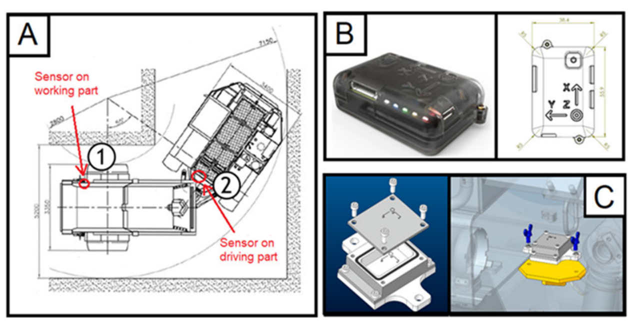


FIGURE 4. A: The location of measurement points, B: NGIMU sensor unit used, C: The method of installation sensor on the vehicle and the steel housing of the device.

Unfortunately, due to measurement in underground mine conditions as well as enclosing the sensor in a protective steel housing, the readings from the magnetometer were useless. Thus, only accelerometer and gyroscope signals have been analyzed. When it comes to the dynamic overloads, the accelerometer measurements are of most use as they describe the vibration levels. Therefore, the main focus was put on data from the Z-axis because it is directly related to machine vibration levels on the vertical axis. Regardless, because of the transmission of vibrations between the axes, X-axis and Y-axis measurements were also analyzed. An example of the waveforms of the analyzed variables is presented in Fig. 5.

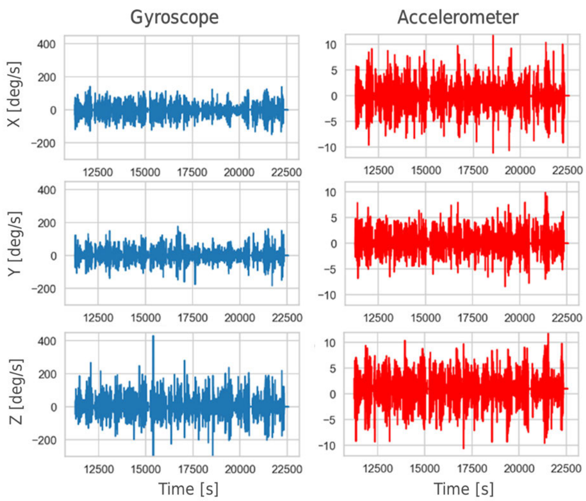


FIGURE 5. Example of waveforms acquired from selected triple axis variables with using the NGIMU sensor, blue – gyroscope, red – accelerometer.

Finally, readings from humidity sensors were deemed useless as they are not related to the machine or the operator and only describe the conditions inside the steel housing. In addition, as the experiments were carried out in underground mines, the humidity of its environment is a very fluent factor and should not be used in this type of analyses. As for the variables utilized, apart from the sample rate little being a lower than declared, the data was of excellent quality with little to no missing values.

C. THE SAMPLE DESCRIPTION

Overall, 3 underground mines (M1–M3) were subdued to the experiments, consisting of 4 mining regions (D1–D4), 7 heavy machinery chambers (C1–C7), and 8 mining divisions (I–VIII). All of this resulted in 19 haul trucks (HT1–HT19) driven by a total of 60 operators. The generalized scheme of the enterprise organization that took part in the experiments is presented in Fig. 6.

Each of the measurements was performed using the same method. Sensors were installed a while before the start of machines' operation. Then such machines worked two full shifts, after which the sensors were dismounted. So, as a sample, we define the data from 2 sensors covering 2 full work shifts. After the completion of one measurement sample, both sensors needed to be recharged before the next

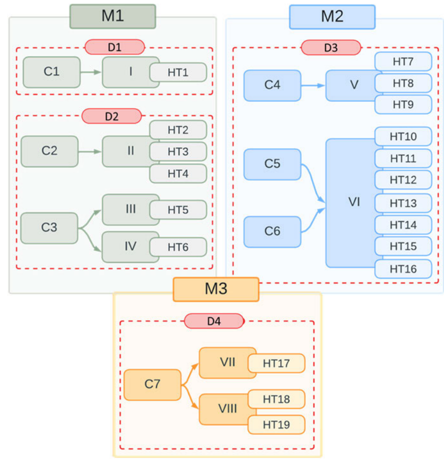


FIGURE 6. Generalized scheme of the mining hierarchy that took part in the experiments.

usage. Unfortunately, due to limitations related to conducting the measurement campaign in the operating conditions of the underground mine, it was impossible to obtain continuous measurements on a daily basis, shift after shift. Most often, the time between measurements (i.e., two working shifts) was 1-4 days.

One of the more meaningful aspects of this research was the study of operator influence on machines' vibrations. In the subsequent sections, the operators are compared in ranking based on proposed methods. Moreover, there is a an indication of the relationship between the operator's driving style and the failure rate of vehicles. To summarize, a quantitative view of data is the presented in Fig. 7.

A greater number of measurements observed in the red group concern the mine, where a very high level of joint failure rate was noted. The HT6 and HT3 are the machines with the lowest mileage between failures. The green group concerns mines with mining divisions where machines are exposed to low, medium, and high overloads. The yellow group, on the other hand, is a mine where road conditions are the best and the level of overloads and joint failures is the lowest.

IV. METHODOLOGY

The dynamic overloads were investigated through machine vibration analysis. Through this process, four main factors with the largest impact on machine vibrations were established. Those factors are: the machine's working environment, the machine operators, the part of the transportation process, and the vehicle equipment. As shown in Fig. 8, each of the factors was treated as a dimension for future analysis. For this task, metrics presented later in this article were established, as well as two supplementary algorithms. The first one was created to estimate machine driving speed, which differed strongly with regard to parts of the process and operator driving characteristics. The second algorithm was created for detecting moments of machine turning (with two

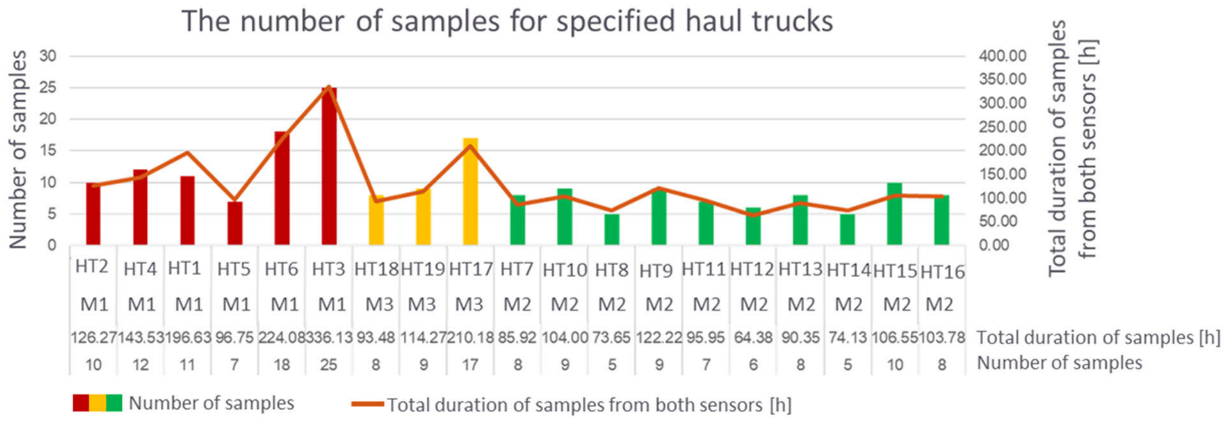


FIGURE 7. Number of samples and duration of samples for each: haul truck and mine department.

types of turns being recognized) and was also connected to the environment (road layout of the mine).

The algorithms were established as a supplementary insight, as all of the metrics utilize only the raw readings (mostly from the vertical axis of the accelerometer). All of the below-mentioned analyses were carried out on signals that were segmented into individual cycles. The segmentation process was carried out by hand, as individual cycle components were only slightly visible in the raw signals. The division of raw signals into cycles and their components introduced a common ground for further analyses, enabling various forms of comparison between them.

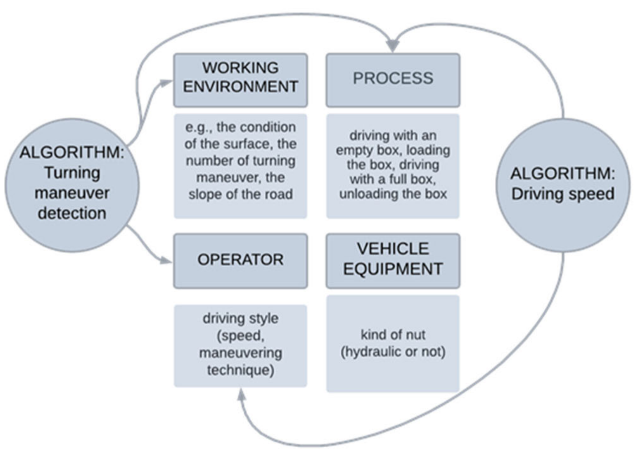


FIGURE 8. Main dimensions that took part in the analysis along with their connection to algorithms.

A. SELECTED MEASURES

Measures used in the analysis of dynamic overloads are presented in Table 1. All of them can be calculated on different scales of segmentation (whole day, one shift, one cycle, one cycle component, etc.), and while they can be applied to all of the signals, they were calculated only for the accelerometer Z axis. The utilized measures were: quantile 0.99, quantile 0.90, quantile 0.95, quantile 0.80, the mean of the 10 highest values, range, and the driving time with low, medium, and high vibrations. Selected measures are calculated for single cycles and operations (separately for both sensors).

TABLE 1. Measures proposed to give insight into dynamic overloads based on vibration.

Measure	Description
Quantile y [g]	Quantile calculated from data, one of: {0.80, 0.90, 0.95, 0.99}. Higher quantiles should correspond to very large, mostly impulsive values and therefore dynamic overloads.
Mean of the 10 highest values [g]	The arithmetic mean of the 10 highest values in the data [1].
Range [g]	The difference between the lowest and the highest value in the data.
Driving time on low vibrations [s]	The number of observations lower than or equal to the first threshold, divided by the number of measurements per second.
Driving time on medium vibrations [s]	The number of observations greater than the first threshold and lower than or equal to the second threshold, divided by the number of measurements per second.
Driving time on high vibrations [s]	The number of observations greater than the first threshold, divided by the number of measurements per second.

Both of the thresholds (mentioned in the above table) are established based on several samples (for haul trucks HT2, HT3, and HT4) and are determined separately for various axes and sensors. The first threshold is the quantile 0.60 of the data, while the second threshold is the quantile 0.9. The established thresholds are shown in Table 2.

All described measures can be used to assess the level of vibration in three axes. The upper quantiles indicate the values of the largest vibrations and, at the same time, do not take into account the most outliers. The average of the 10 highest values allows one to analyze the largest vibrations along with

TABLE 2. Thresholds for measures: driving time with low/medium/high vibrations.

Sensor	Threshold	X-axis	Y-axis	Z-axis
Front	1	0.0833	0.0719	0.0995
	2	0.3272	0.1668	0.4442
Back	1	0.0991	0.0912	0.1168
	2	0.3522	0.2646	0.5854

outliers. The range defines how much the amplitudes change. In turn, the driving time at individual vibration levels shows how long the machine was exposed to high, medium, or low overloads. From all of the above-mentioned measures, it was found that two of them are especially crucial when it comes to dynamic overloads. Those measures were the mean of the 10 highest values in the Z axis of the accelerometer, along with a percentage of driving time on high vibrations.

B. TURNS MANEUVERS IDENTIFICATION

For the turn detection (i.e., moments in time when the haul truck turns) the Z-axis readings from a gyroscope were utilized. However, firstly, the raw angular velocity measurement from a gyroscope needed to be processed to form the yaw rotation angle. This action can be done using the numerical integration presented in (1).

$$\psi\,(\mathrm{t}) = \int_0^{\mathrm{T}} \omega_Z\,(t)\,dt, \tag{1}$$

where ψ is the Yaw angle as a function of time t and ω_Z is the angular velocity in the Z-axis. From this point, there are many possible ways to detect the turn. In this particular research, the algorithm presented in [24]. The authors of the selected publication verified several classification methods and finally presented a method based on the random forest, which was incorporated into the presented analyses. The simplified scheme of the algorithm is presented in Fig. 9. The yaw angle data from one shift (6 hours) is used as the algorithm input. This vector is then split into one-second fragments from which a set of measures is calculated (standard deviation, range, median, interquartile range, and kurtosis). Such statistical sample is then used to make a prediction using a random forest classifier. The output of the classifier is a categorical variable that can take 3 possible values: 0 – the vehicle did not turn during the recorded segment; 1 – the vehicle did a turn of 40°-70°; or 2 – the vehicle did a turn of 70°-100°. To train such classifier, a selection of recoding was utilized, where all turns in categories 1 and 2 were marked by a human.

Determining the vehicle's turning moments enables a more accurate analysis of the haulage path. For example, more turns can cause more dynamic overloads, especially when there are difficult conditions such as narrow corridors.

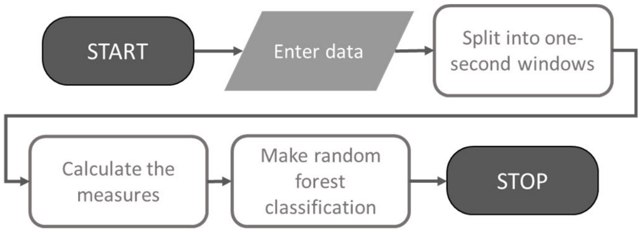


FIGURE 9. Simplified procedure for turns identification.

C. ESTIMATION OF VEHICLES SPEED

Possible speed levels are tightly connected to the environment in which the machines are currently working. Unfortunately, most of the machines were not covered by the monitoring systems (except for HT1, HT17, and HT18) which include the measurement of this variable. Instead, a very crude approximation of the mean speed can be obtained by dividing the length of the haulage path by the time of each haulage operation. Information about haulage routes is extracted from the CMMS system utilized by the mining enterprise. The time from each cycle is the length of the driving operation acquired by the previously mentioned segmentation. It should be noted that the haulage lengths extracted from the system may be affected by errors. Speed is another factor that may affect dynamic overloads, so it is worth including this parameter in the analysis. Driving at high speed with an empty box can increase its value.

D. OPERATOR RANKING

The ranking of operators was performed with the developed metric connected with Z-score statistics calculated for (a) the mean of the ten largest amplitudes and (b) the ratio of standard deviations for the driving time with high and medium vibrations. Their position in the ranking is determined based on this score. The score takes into account the fact that one operator can drive several trucks. Only measurements from the rear sensor are considered. The score (for the selected axis) is given by the following equation (2):

$$SCORE = 200 - \frac{1}{2} \cdot \left(\sum\nolimits_i w_i \cdot \left(\frac{\bar{x}_{op,i} - \bar{x}_i}{\sigma_i} + 100 + \frac{d_{op,i}}{d_i} \cdot 100 \right) \right) \tag{2}$$

where: i determines the vehicle index; w_i is the weight of the i-th vehicle; $\bar{x}_{op,i}$ describes the mean of the 10 highest values for the selected operator and i-th vehicle; $\bar{x}_i$ is the mean of the 10 highest values (of vibrations) for the i-th vehicle (and all operators); $d_{op,i}$ is the sum of the ratio of the driving time with high and medium vibrations for the selected operator and i-th vehicle; d_i is the sum of the ratio of the driving time with high and medium vibrations for i-th vehicle (and all operators); and finally, σ_i denotes the standard deviations of the 10 highest values for i-th vehicle (and all operators).

The operators for whom the length of the collected samples was inadequate (shorter than the average for all measurements) do not receive the score. The score is not calculated when the number of cycles performed during the operator shift is too small. Thanks to omitting operators with insufficient data, it is possible to avoid the situation where the score would be overstated by a single measurement (that may or may not determine the operator's driving behavior).

Receiving a score of 100 by an operator means that he does not stand out from other operators driving the same vehicles. A score above 100 means that the statistical values of the operator are lower than the values for the population (results from the vehicles that the operator was driving). Therefore, it can be assumed that his driving style is more subtle than that of operators who obtained lower ratings.

E. THE FACTOR ANALYSIS

Factor analysis is a useful approach that enables one to identify which features are the most influential in a particular set of variables. In this paper, this analysis is applied to examine which factors affect vibrations the most. Based on previous conclusions (concerning statistical analysis), such analysis was carried out by connecting the model with two measures: the mean of the ten highest values (model 1) and the percentage of the driving time with high vibrations (model 2). For this reason, two random forest classifiers were created, one for each measure. The following independent variables were used in each of the two models: process, operator, vehicle, number of cycles, heavy machinery chamber, mine region, mine.

The quality of the fit can be assessed by calculating the mean square error. After the initial starting calculation, the individual factors are sequentially excluded from the models. After each iteration, the MSE metric is recalculated. This operation allows one to check how much the quality of the fit changes. For instance, if the factor ''process'' is removed and the quality of the model does not change, then it can be concluded that the ''process'' is not influential. On the other hand, for significant factors, the quality of the model deteriorates after excluding the procedure. Hence, their presence affects the model and results, which is an important factor for estimating the level of dynamic overload.

V. REAL DATA ANALYSIS

Performing a full multidimensional analysis requires first determining the key factors influencing the observed dynamic overloads. Therefore, both of the models are tested on actual data from the Z-axis of the accelerometers, and their metrics are presented in Table 3.

These results confirm that the models can be used to evaluate the significance of variables (and their impact on the resulting metrics. Therefore, in the next stage, all of the variables can be sequentially removed, and the MSE of the models can be monitored to estimate their influence on the metrics. Results from that action are presented in Fig. 10.

TABLE 3. Comparison of the resulting metrics obtained for both models.

Property of the Model	MODEL 1	MODEL 2
Range	0–13 g	0–20 %
MSE	1.445	0.11
Mean error	0.895 g	1.72 %
% of the variance explained by the model	74.7%	76.8%

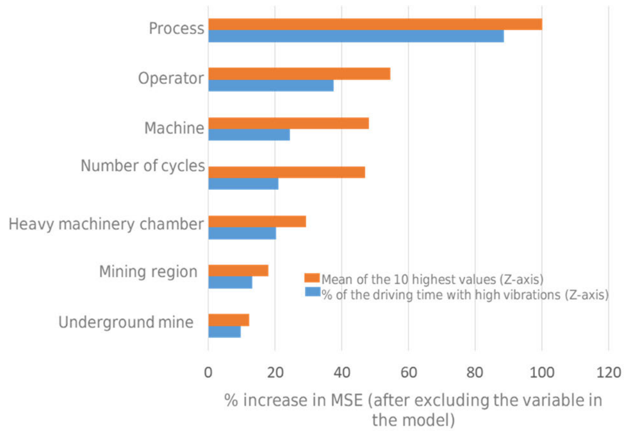


FIGURE 10. Importance of the variables on the vibration level.

Both models agreed unanimously that the most influential factor is the type of operation performed (process). This is an expected result, as it is intuitive to think that larger vibrations occur when a machine drives with an empty box than with a packed box. In addition, signal fragments related to loading the box have characteristic peaks (shocks that are classified as large vibrations). The method showed that the second most influential factor is the operator. However, this information is not fully reliable because each operator usually works in one place and on one machine. Therefore, such information is already partially coded in vehicle and workplace variables, which in turn lowers their importance. The method would be more reliable if each operator would move to different machines and the machines would move in various regions. Unfortunately, for various reasons, this action was impossible to perform, even on a smaller sample.

A. COMPARIVE ANALYSIS–MINES, MINING DEPARTMENTS, AND PROCESSES

The comparative analysis starts with an examination of the mine's influence on the vehicle's vibration characteristics. Previously, it was mentioned that the most significant differences can be seen at the rear sensor (Z-axis); therefore, all metrics and values in this section are presented only for this axis. Mining departments are compared using a percentage of driving with a high vibration metric calculated for each cycle component. Such a comparison is presented in Fig. 11, and it is clearly seen that the mines and mining department do have an impact on dynamic overloads. The vibration level in M1-D1 and M3-D4 is lower than for the other mining departments, and there are differences between the areas within one mine (much more outliers in M1-D2 than in M1-D1). However, one possible cause for that is that samples from D1 come from a single haul truck, which can translate to a smaller number of outliers associated with differences between machines. Overall, the results are the same as expected, as different mines and mine departments are managed differently and possess different environments (e.g., road conditions that translate to vibration and make it possible to acquire more speed).

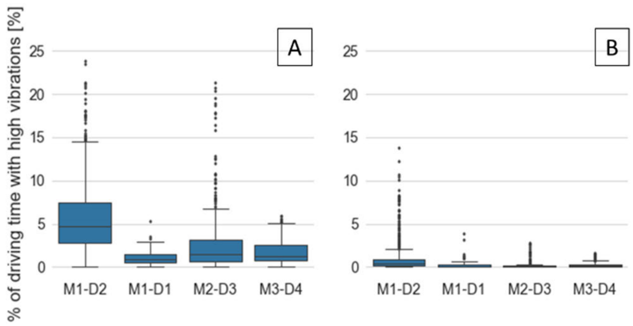


FIGURE 11. Percentage of driving time with high vibrations, A - sensor on the working unit, B - sensor on the driving unit.

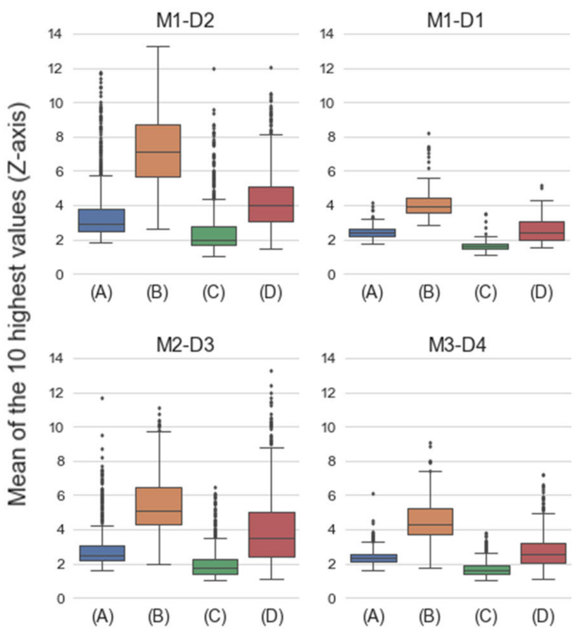


FIGURE 12. Comparison of dynamic overload rates between mining departments at the different processes of the cycle (mean of the 10 highest values for Z-axis accelerometer located on the working unit); (A) driving with full box, (B) driving with an empty box, (C) dumping material, (D) loading of the cargo box.

Similar analyses were carried out using the metric describing the ten highest values. Results from such a study, divided

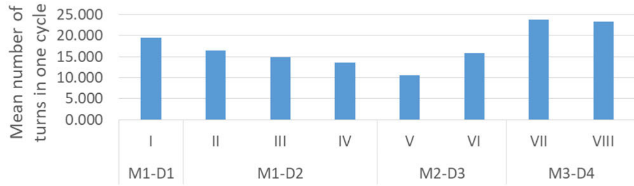


FIGURE 13. Mean number of turns in one cycle per mining regions and heavy machinery chambers.

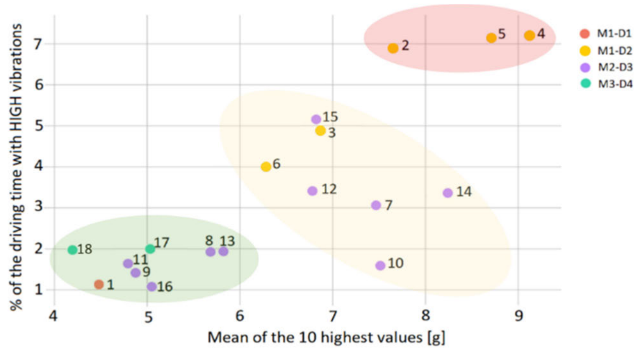


FIGURE 14. Scatterplots of the centroids for particular haul trucks (including mining departments). Measures calculated for the Z-axis accelerometer located in the working unit.

not only for the mines but also for different cycle components, are presented in Fig. 12. The general values of these metrics for the whole mine department are consistent with the previous metric. As for the processes, driving with an empty box and loading generate substantially more dynamic overloads than their counterparts (driving with a full box and unloading). Overall, driving with an empty box can always be considered as a process with the highest dynamic overloads. On the contrary, unloading can be described as a process of least vibrations.

To better investigate the working places, it was decided to check the average number of turns made by machines in one cycle in individual heavy machinery chambers in each mining region (Fig. 13). It can be seen that the most turns are in M3-D4 and the second place is in M1-D1. As shown above, these two mining regions also have the smallest values of dynamic overloads. This means that a higher number of turns does not directly affect higher dynamic overloads.

B. THE VEHICLE AND ENVIRONMENT RELATION AND ITS IMPACT ON OVERLOADS

The previous analysis confirmed the impact on the work environment. Therefore, the next step was to access the influence of the machine. This was done by comparing all haul trucks on the plane constructed using two metrics. To achieve that task, for each machine, all its samples were taken, and a single centroid was calculated from them. In that way, all of the machines can be visualized on a single plot (Fig. 14) without too much noise or data overflow. It can be seen that machines generally fall into one of 3 groups: small, medium,

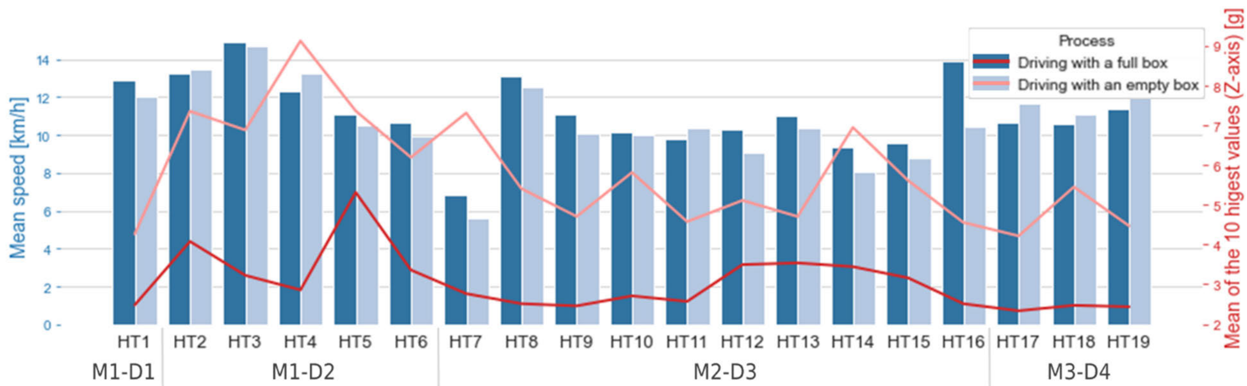
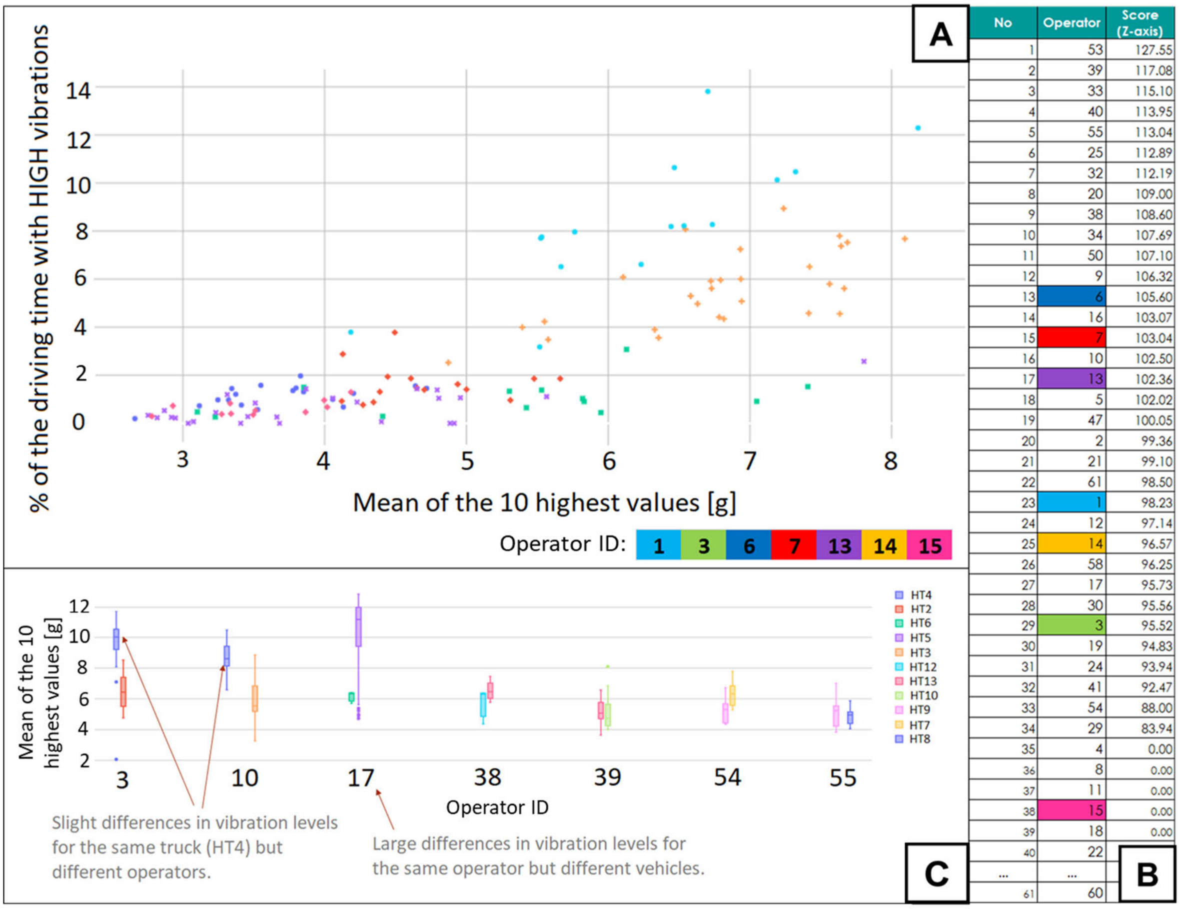


FIGURE 15. Comparison of the average speed and the mean of the 10 highest values for the Z-axis accelerometer located in the working unit for various machines, divided into driving with an empty and a full box.



No	Operator	Score (Z-axis)
1	53	127.55
2	39	117.08
3	33	115.10
4	40	113.95
5	55	113.04
6	25	112.89
7	32	112.19
8	20	109.00
9	38	108.60
10	34	107.69
11	50	107.10
12	9	106.32
13	6	105.60
14	16	103.07
15	7	103.04
16	10	102.50
17	13	102.36
18	5	102.02
19	47	100.05
20	2	99.36
21	21	99.10
22	61	98.50
23	1	98.23
24	12	97.14
25	14	96.57
26	58	96.25
27	17	95.73
28	30	95.56
29	3	95.52
30	19	94.83
31	24	93.94
32	41	92.47
33	54	88.00
34	29	83.94
35	4	0.00
36	8	0.00
37	11	0.00
38	15	0.00
39	18	0.00
40	22	
...	...	
61	60	

FIGURE 16. Rankings for operators and their relation with machines - A) The scatterplots for particular operators of HT2, and the ranking of the operators. Measures calculated for Z-axis accelerometer located in the driving unit. B) Table with score values for each operator. C) The comparison of the vibration levels (the mean of the 10 highest values; the sensor located on the working unit) for different operators and machines.

or high dynamic overloads (marked on the plot as green, yellow, or red areas).

Then, it was decided to determine the average speed for each machine and compare it with dynamic overloads occurring on the working unit. Fig. 15 shows the mean speed and the mean of the 10 highest values with division into two processes of the machine's cycle: driving with an empty and a full box. It is visible that the speed is not directly proportional to dynamic overloads, but some relations are worth noting. Usually, the speed of driving with an empty box is slightly lower than the speed of driving with a full box. The exception is the whole M3-D4, where probably better road conditions allow for faster driving with an empty box. Another case is machine HT4, for which there is the highest value of the dynamic overloads statistic when driving with an empty box. Driving too fast with an empty box can, in this case, cause high dynamic overloads. In another respect, the HT16 stands out as it drives much faster with a full box than with an empty one. However, it does not seem to have a significant impact on overloading. The lowest speeds are visible for the HT7 machine, which does not mean small overloads. This shows that speed, and especially its adaptation to the conditions, can have an impact on dynamic overloads, but it is not obvious due to other factors.

C. THE HAUL TRUCK AND OPERATOR RELATION AND ITS IMPACT ON THE OVERLOADS

For a presentation of the relationship between a haul truck and its operators, an HT2 was chosen. This specific vehicle is characterized by very high vibrations on the rear sensor while driving with an empty box. For this particular machine, the high vibrations observed when driving empty are not present when the vehicle is loaded. This is with the exception of Operator 1, whose driving style probably causes additional overloads for the sensor on the working unit. In addition, one sample for this operator was recorded during a machine failure; therefore, it can influence his score. As mentioned earlier, vehicle operators are compared using ranking. The one overall rating is the arithmetic mean of the scores from all axes. As cycle operations are statistically significant, it is possible to make the operator's score depend on them. One of such rankings is presented in Fig. 16.

The main tool for comparison is the scatterplot with the ranking of operators (rating concerning the Z-axis). Operators with higher vibrations get fewer scores, and one can clearly see that some of them have generally elevated values. When one haul truck is being driven by more than one operator, it is possible to put them together and compare the results with the use of boxplots. Usually, such comparisons point out that vibrations are similar and mostly depend on the machine that is being driven. Nevertheless, there are cases when such a comparison shows an outstanding difference, pointing out that one operator's driving style is good or bad enough to overcome the impact of the machine.

VI. CONCLUSION

The main purpose of the research was to examine the distribution of dynamic overloads on haul trucks and their factors in various operating conditions that could explain significant differences in the frequency of failures between mining departments in three KGHM underground mines. Joint failures are unfavorable not only from an economic point of view but also pose a real threat to the life and health of the operator himself as well as employees in the vicinity of the machine. In the study, it was decided to use a non-invasive inertial measurement unit. Since it was impossible to mount the sensor on the joint itself, it was decided to use two sensors on one machine. One was monitored on the drive unit and the other on the working unit. The main objective was to observe the mutual behavior of these units in three axes in different road conditions, machine operations, and approximate recognition of the distribution of forces acting on the unit and the machine's joint. Due to the fact that damage to horizontal joint is typically fatigue-related, the main emphasis in the work was placed on examining a number of regularities of dynamic overloads, especially those with impact action. Three-axis accelerometers and three-axis gyroscopes were used as the main source of data on overloads and the reaction of forces acting on the joint in various operational situations of the machine. Identification of the distribution of overloads and the sources of their formation required proposing an appropriate statistical description. In order to recognize the factors influencing the form of the recorded overloads and the regularities accompanying them, it was necessary to conduct a multidimensional analysis by:

1. signal segmentation for the purposes of identifying the components of the operation (working shift, haulage cycle, loading, driving with a full cargo box, unloading, driving with an empty cargo box, operational standstill, turning the machine, driving on an access road);

- selection of representative samples (operator, region, mining department, critical machine, access road, failure, looseness, etc.);
- data processing in various contexts and configurations.

The key analytical directions included:

1. Factor analysis.
2. Comparative analysis between the mines, their regions, and operations.
3. Testing the relationship between the machine and the workplace at the level of recorded overloads.
4. Examination of the machine-operator relationship to the level of recorded overloads.
5. Testing the relationship between average speed and number of turns per cycle to the level of recorded overloads.

The level of influence of variables: operation, operator, vehicle, number of cycles, chamber, region, and mine on the level of vibrations was tested using random forests based on statistics: the average of 10 maximum values in the Z axis and the percentage of work time at high vibrations. The most informative variable is the operation. This result confirms the relationships noted during the preliminary analyses (e.g., greater vibrations when driving with an empty box than with a full one). The method showed that the vibration level is next affected by the operator. However, it was indicated that this study has some limitations, mostly because each of the operators during the tests usually worked in one place and on one machine, so this information is already included in this variable. This lowers the importance of vehicle and workplace variables. Thus, the impossibility of determining the actual weights of the impacts of individual variables with this method was demonstrated. Additionally, attention should be paid to a number of factors that will negatively affect the interpretation of the results:

- There is no continuous monitoring of all machines at the same time.
- Lack of measurements of the work of a single machine in all areas of the mines subjected to the study.
- Operators do not drive all machines in all areas. So the impact of the workplace is also included in the operators and the machine.
- Lack of current information about looseness and damage to the joint.
- No measurements directly from the machine's joint.
- No monitoring of tire pressure parameters.

Nevertheless, the interdependence of factors and the need to perform an exploratory analysis were shown. Further analysis was necessary, taking into account the comparisons: operator – machine, machine – workplace, and a number of other variables. The general level of vibration recorded in individual mines was compared, taking into account the regions and departments present there. A large diversification in the level of overloads was shown both between the mines and the mining departments located there. This suggests a predominant influence of the workplace on dynamic overloads. A comparative analysis of the regions was carried out in terms of the size of the overloads observed in various operations of the vehicles. It was noticed that one region clearly lags behind in all types of operations of the haulage cycle compared to the areas with the normal level of overloads. Using the statistics of dynamic overloads, a comparison of machines was made, taking into account their place of work. It has been observed that, to a large extent, machines can be grouped by regions. When comparing the level of vibration measured during the work of different operators on the same machines and mining areas, we usually do not observe large differences in the values. There are individual cases when the level of vibration for selected operators is much higher than for the rest. It is possible, however, that the technical condition of the machine has an impact on this. Some such cases have been correlated with failure. It seems that the machine itself has a greater influence on the vibrations than the operator.

The findings presented in this research have important implications for the mining industry, and possibly, other industrial areas with heavy-duty vehicles. Understanding the behaviour of dynamic overloads and their relation to certain work-related factors is crucial to ensure the safety of humans and machines. Companies can either use relations presented in this paper, that were established on an example of KGHM mines or perform a similar analysis on their own. In the authors opinion, the main application of this study lies in the implementation of policies based on the results obtained.

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